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Value of information using calibrated geothermal field data

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ABSTRACT

Value of information (VOI) quantifies how useful a particular information source is when making a decision with an uncertain outcome and can be used to justify the purchase of additional data when exploring for geothermal resources. Here we present a preliminary VOI evaluation that utilizes calibrated field data to estimate the reliability of magnetotellurics (MT) data to define the boundaries of the geothermal resource. The field data is considered calibrated because production parameters are available and are approximately collocated with the geophysical data. Specifically, we consider a 3D electrical conductivity model constructed from 3D MT data, which overlap 23 wells that have steam flow rate data. Typically, MT data are used to detect and image the electrically conductive clay cap which can be indicative of geothermal alteration occurring just above the resource. Therefore, the interpretation of 3D surfaces (top and base of the clay cap) is critical in evaluating the effectiveness of the MT to define potential geothermal resources. Our preliminary results show that the VOI estimates for this particular decision scenario are not that sensitive to the different possible interpretations of the clay cap. The work develops the analytic framework and workflow needed for evaluating data to be used in geothermal decisions.

1. INTRODUCTION

The value of information (VOI) considers how relevant and reliable any particular information source is, and quantifies its value when making a decision with a highly uncertain outcome. VOI can be used to justify the costs of collecting and processing the planned data. It has been used in oil exploration (see review by Bratvold et al, 2009). We apply it here to geophysical data from a geothermal field. Previous work (Trainor-Guitton et al., 2013; Trainor-Guitton, et al., 2013) tested the applicability for geothermal exploration using synthetic datasets.

VOI is method from the field of decision analysis. Decision analysis concepts are often described in terms of lotteries and prizes (Pratt et al, 1995). By choosing to drill or not, a decision maker is choosing whether or not to participate in a lottery with certain perceived chances of winning a prize (drilling into a profitable reservoir); however, this lottery also involves the chances of losing money (drilling into an uneconomic reservoir). VOI estimates the possible increase in expected utility (winning a lottery with a bigger prize) by gathering information before making a decision, such as where or if to drill a production well. In its simplest form, the VOI equation can be expressed as:

$$VOI = V_{with\ information} - V_{prior} \quad (1)$$

where V is the value, the metric used to quantify the outcome of a decision. The higher the value, the more “successful” an outcome of a decision is.

This manuscript describes a preliminary methodology to estimate the efficacy of MT via an existing, calibrated field dataset. We consider the decision to drill for a possible geothermal resource at a specific location. We simply consider the decision of “to drill or not.” It is possible to extend the methodology to the more complex decision of “where to drill.” We assume that the decision outcome only depends on the possible steam flow of a reservoir.

Our work illustrates the implementation of a VOI methodology given the uncertainties of geothermal exploration and multiple interpretations of the clay cap from a 3D MT inversion, and we utilize an existing dataset of steam flow measurements to deduce trends between steam flow and electrical conductivity, thereby using the past performance of the geophysical technique to predict steam flow. The results of study will serve as a guide on deciding whether to collect 3D MT for steam flow estimation in other areas.

We consider how well the clay cap, as delineated by a 3D MT data inversion, can indicate magnitude of the steam flow by utilizing a dataset from an operating geothermal field. This MT inversion provides spatial information on the subsurface structure that may be related to the production potential of the geothermal resource. The electrically conductive materials imaged by MT are created by geochemical alteration when hot fluids circulate within subsurface geologic units (Gunderson, et al., 2000). However, if the hot fluid source ceases to exist, the electrically conductive material will remain, thus a clay cap does not guarantee current geothermal activity (Karlsdóttir et al., 2012).

This paper is organized as follows. First, the steam flow data set will be described. Second, we will briefly describe the MT inversion. The result of the inversion is a 3D cube of electrical conductivity which is used to infer the location and margins of the clay cap. The boundaries of the clay cap may represent the potential margins or boundaries of the geothermal reservoir. Third, we will describe the different assumptions used to determine the clay cap and colocation between the electrical conductivity of the clay

cap and a steam flow measurement. The various conductivity and spatial thresholds produce various interpretations of the “calibrated dataset.” Fourth, these multiple interpretations will serve as our estimate of MT’s reliability to delineate the boundaries of the geothermal reservoir, which we assume is linked to the steam flow magnitude. Finally, we will calculate VOI’s (values of information) utilizing these reliabilities.

2. THE DATA SET

2.1 Steam flow measurements

The steam flow dataset contains the average production over one year for 23 different wells. The steam flow data approximately spans an area of 2.6 km by 4.2 km and a depth range of 600m to 1800m below the surface. Figure 1 displays a histogram of these steam flow measurements. The steam flow measurements are composite flows for all feed zones from each well.

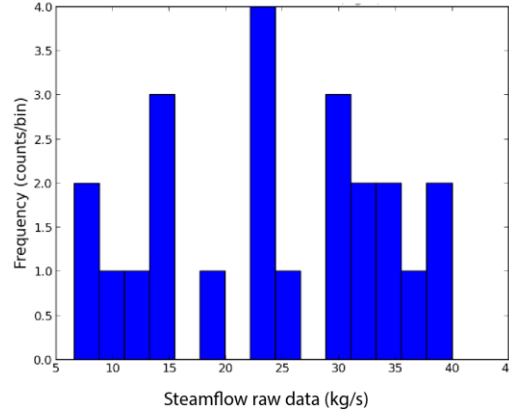


Figure 1: Histogram of steam flow data from 23 wells

For this preliminary VOI evaluation, we categorized the *steam flow magnitude* into seven groups or bins, represented by θ_i :

$$\theta_i \in \begin{cases} 7, & \theta \geq 30 \text{ kg/s} \\ 6, & 25 \leq \theta < 30 \text{ kg/s} \\ 5', & 20 \leq \theta < 25 \text{ kg/s} \\ 4, & 15 \leq \theta < 20 \text{ kg/s} \\ 3, & 10 \leq \theta < 15 \text{ kg/s} \\ 2, & 5 \leq \theta < 10 \text{ kg/s} \\ 1, & 0 \leq \theta < 5 \text{ kg/s} \end{cases} \quad (2)$$

We define our prior uncertainty with respect to steam flow production using these steam flow categories. Let us represent this by

$$\mathbf{z}(\theta_i) \quad i = 1, \dots, 7, \quad (3)$$

where vector \mathbf{z} represents the non-dimensional steam flow categories that may be realized from production wells. Future work will incorporate spatial aspects of this steam flow possibility. The steam flow categories can be used to represent the economic (value) outcome of a drilling decision at any location (x, y, z) .

2.2 Interpretations of Clay Cap: different conductivity thresholds

We have one 3D model of conductivity inverted from a MT dataset that utilized 85 measurement stations for the area overlying where the steam flow measurements were made. We use this inversion model to determine possible relationships between the electrical conductivity property and the steam flow magnitude. Typically, the high conductivity layer can be used to estimate the likely margins of the geothermal system (Cummings, 2009). We attempt to assess whether the thickness and conductivity information of the clay cap can be used to distinguish between higher and lower steam flow.

As we assume that the “clay cap” margins can be used to infer the boundaries of the geothermal resource, we define a conductivity threshold in order to delineate the location and thickness of the clay cap. We use a bottom threshold value of $\sigma=0.12$ S/m. Thus, a top and bottom surface is defined where the electrical conductivity begins to decrease from the threshold value of $\sigma=0.12$ S/m. The resulting cap is pictured in Figure 2.

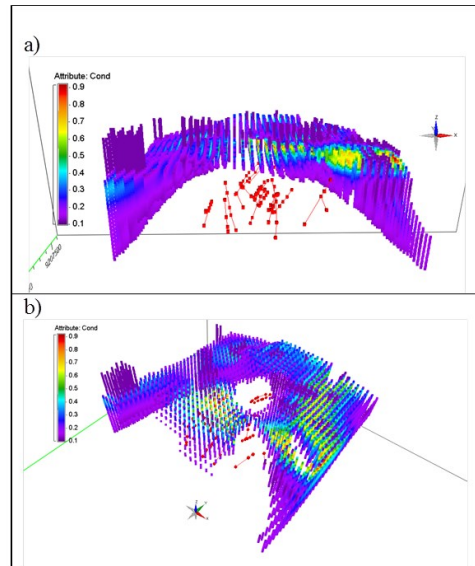


Figure 2: a) Cross sectional view and b) top view of clay, defined by threshold $\sigma=0.12$ S/m. Steam flow measurement locations shown in red.

2.3 Defining “co-located” electrical conductivity and steam flow

Next, we determine which conductivity locations within the clay cap that can be correlated with the steam flow measurements. We suggest that steam flow measurements closer to the cap are more likely affecting the conductivities and geometry of the clay cap. Therefore, we expect a clearer relationship between the steam flow measurements that are closer to the clay cap.

We begin by defining 625m as the maximum distance between a steam flow measurement and any point within the clay cap. We choose this distance because it represents the lower quartile of all distances between the clay cap conductivities and steam flow locations. Figure 3a) displays the midpoint of Well 15 as a brown box along the well path (red) and the conductivity values of the clay cap. First, the location of the closest conductivity measurement to the well midpoint is determined. Then, the neighboring conductivity values in the clay cap are averaged within a radius of 100 m to compare to the steam flow of that well. Figure 3b) displays only the conductivities measurements that are within 100m of the closest conductivity point for Well 15.

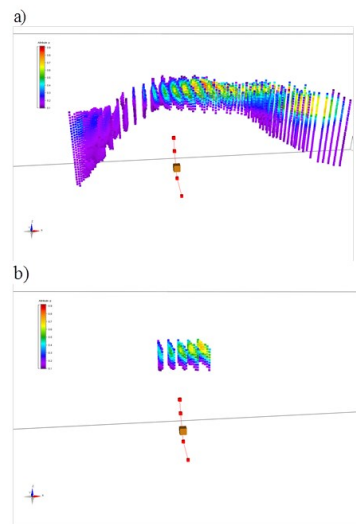


Figure 3: a) Well 15 midpoint (brown box along red path) with conductivities of clay cap. b) Only the conductivities within 100m of the closest conductivity point to Well 15's midpoint.

This is repeated for any steam flow-clay cap pair that are less than 625m away. Figure 4a plots the geometric average of these neighboring conductivities versus the nearest steam flow measurement. Six of the 23 steam flow measurements locations were within the maximum threshold of 625m. Of this set, the conductivities show a slight positive correlation (0.28) with steam flow.

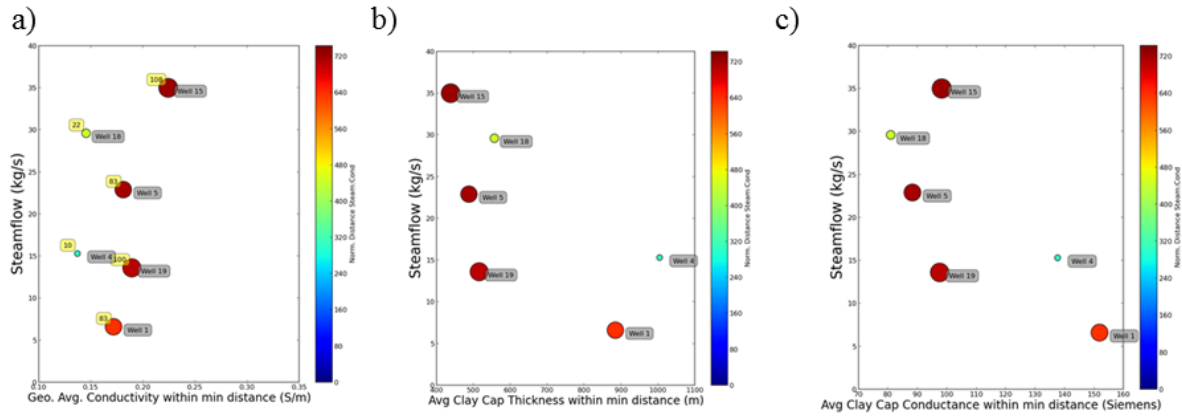


Figure 4: 2D scatterplot of co-located a) electrical conductivities (geometric average) b) thicknesses (arithmetic average) and c) conductance (all from 0.12S/m clay cap) and steam flow (*maximum distance 625m*). The size of the symbols reflects number of conductivities and the color the relative distance

This same process is done for the clay cap thickness at these neighboring locations. Figure 4b displays the arithmetic average of the clay cap thickness versus the 6 steam flow measurements, and Figure 4c displays conductance (the product of conductivity and clay cap thickness). Unlike Figure 4a, these two plots now show a negative correlation with steam flow: -0.67 and -0.73 respectively. The negative correlation of steam flow with conductance (which is dominated by the thickness) is expected since greater temperatures ($>200^{\circ}\text{C}$) will alter the highly conductive smectite clays into more resistive illitic or chloritic clays (Ussher et al., 2000). The clay cap is defined on the basis of conductivity and therefore likely represents only the distribution of smectite. Places that have been altered to illite will not be included. Thus, if the clay cap is capturing only the higher conductive smectite, one would expect a thinner cap where the permeability is higher, allowing for hot temperatures to circulate and alter smectite to lower conductive illitic.

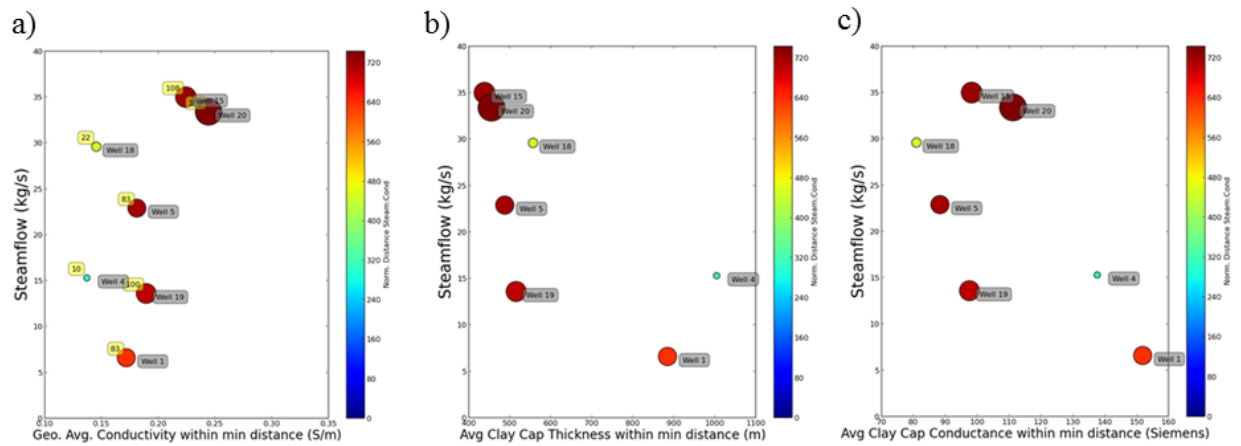


Figure 5: 2D scatterplot of co-located a) electrical conductivities (geometric average) b) thicknesses (arithmetic average) and c) conductance (all from 0.12S/m clay cap) and steam flow (*maximum distance 650m*). The size of the symbols reflects number of conductivities and the color the relative distance

To test how sensitive these correlations are to the maximum distance set, the same analysis is done such that co-location can be defined up to 650m. Figure 5 a), b) and c) displays the cross-plots of the geometric mean of conductivities, arithmetic mean of thickness and the conductance versus 7 steam flow measurements (increasing from 625m to 650m adds one well). The respective correlation coefficients are 0.32, -0.72, and -0.65. Overall, they are quite similar to that of the colocation defined by 625m.

Next, we tested how sensitive these results are to the threshold which defines the clay cap. We now defined the clay cap with the threshold of 0.1 S/m. This clay cap, shown in Figure 6, is slightly thicker than the clay cap defined by the threshold of 0.12 S/m (Figure 2).

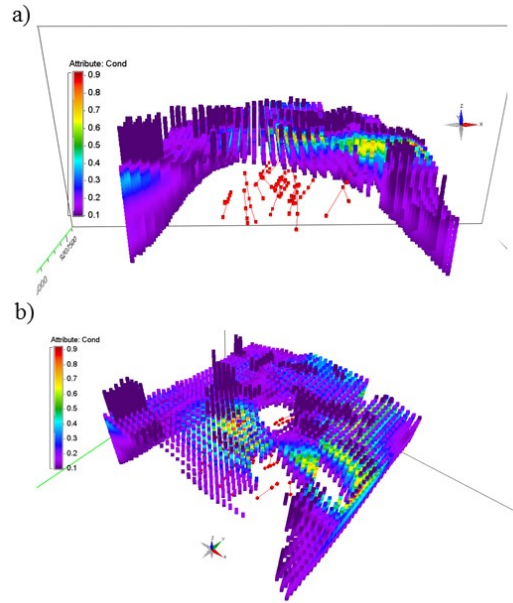


Figure 6: Cross sectional view of clay cap from the inversion that imposes fault boundaries defined by threshold $\sigma=0.10$ S/m. Steam flow trend shown in transparent color.

This thicker clay cap produces more pairs of steam flow/conductivity location pairs when using the maximum distance of 625m. As shown in Figure 7 a), b), and c), eight steam flow measurements are plotted with their neighboring conductivities. The resulting correlations coefficients are 0.25, -0.61, and -0.7. The correlation is slightly less positively correlated for the conductivities and less negatively correlated for thickness and conductance than that of the other clay cap.

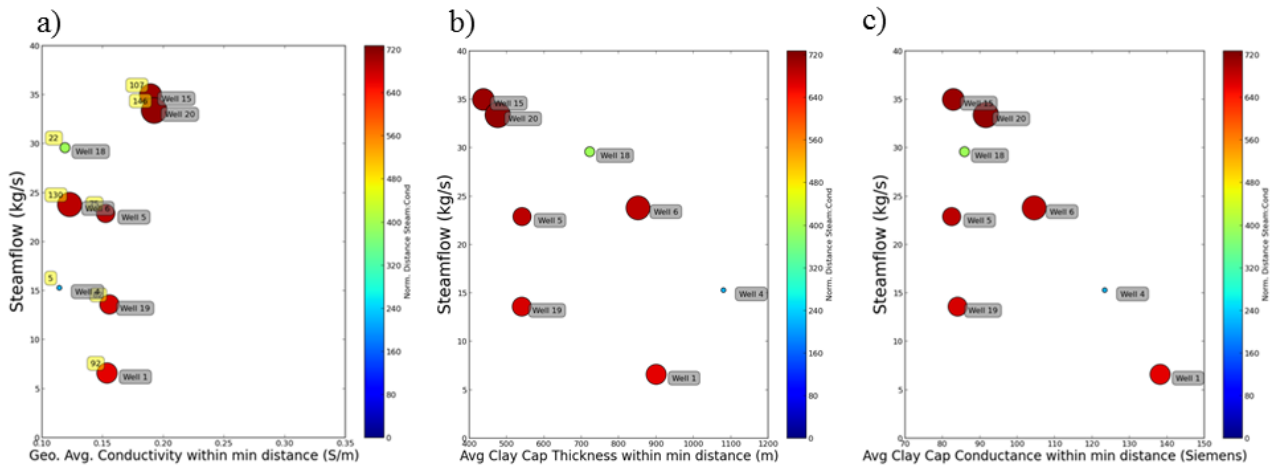


Figure 7: 2D scatterplot of co-located a) conductivities (geometric average) b) thicknesses (arithmetic average) and c) conductance (all from 0.10S/m clay cap) and steam flow (maximum distance 625m). The size of the symbols reflects number of conductivities and the color the relative distance

Lastly, we repeat the same for the maximum distance set at 650m for the clay cap of 0.10 S/m. Now eleven steam flow measurements are located close enough to the clay cap. The resulting correlation coefficients are 0.26, -0.26 and -0.2. The thickness and conductance correlations have significantly changed from the three other colocation definitions. Figure 8 a), b), and c) display these results.

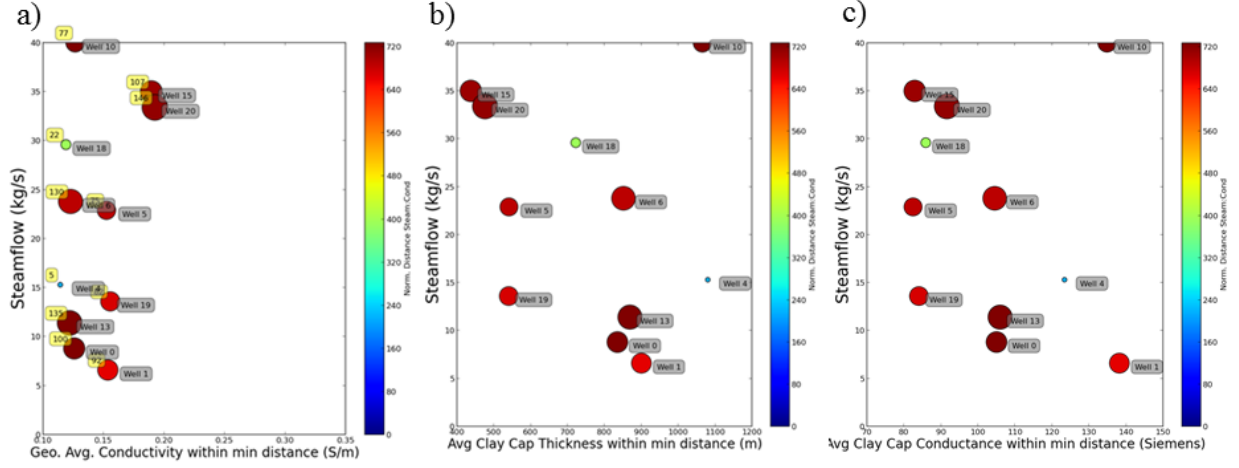


Figure 8: 2D scatterplot of co-located conductivities (geometric average of neighboring values in 0.10S/m clay cap) and steam flow (maximum distance 650m). The size of the symbols reflects number of conductivities and the color the relative distance.

2.4 Establishing estimations of the data reliability/likelihood: How well does the conductance of the clay cap distinguish the steam flow categories?

As described in the Introduction, a data reliability or likelihood is necessary to evaluate VOI. The reliability quantifies the uncertainty in the relationship between the electrical conductivity and the steam flow magnitude. We have two interpretations of the clay cap from the 3D MT inversion. In order to have sufficient measurements to compute some statistics for the data reliability, we will use all conductivity measurements used to calculate the means on the x-axes of Figures 3-8 and 10-15.

The data likelihood (which is also the reliability) is expressed as:

$$Pr(G = g_j | \theta = \theta_i) = \frac{c_{ij}}{\sum_j c_{ij}} \quad (4)$$

$$i = \{1, 2, 3, 4, 5, 6, 7\} \quad j = 1, \dots, J$$

where j indexes the bins of the electrical conductance (g), and c_{ij} represents the count of measurements that belong to steam flow bin i and conductance bin j . The denominator, $\sum_j c_{ij}$, represents normalization by the sum of all data points within that conductance bin.

We will present the data reliabilities for the conductance property only as defined by the 650m threshold. The data reliability given the clay cap defined by threshold $\sigma=0.12$ S-m (Figure 2) is shown in Figure 9. Figure 9 displays all the individual conductance's that went into the geometric average (seen in Figure 4c) plotted in their respective "co-located" steam flow category (Equation 2). The histograms of Figure 9 show the raw counts for each bin (c_{ij} in Equation 4,) which are *not* normalized by the sum of all data points within each conductance bin ($\sum_i c_{ij}$). Wherever any particular conductance bin is represented in more than one of the seven steam flow categories, this signifies ambiguity (uncertainty) in the steam flow-conductance relationship. Conversely, according to Figure 9, a conductance less than 40S indicates that the steam flow is greater than 35 kg/s exists at that location with 100% likelihood since no other steam flow category exhibited that low of a conductance. Thus, there is not steam flow overlap for conductance bins $<40S$.

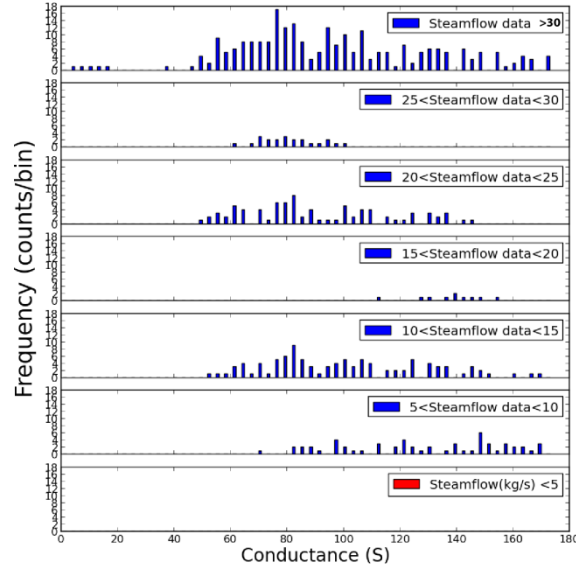


Figure 9: Data likelihood/reliability of clay cap defined by 0.12S/m conductance within 650m to infer steam flow magnitude categories. X-axis represents the clay cap electrical conductance (S).

Similarly, Figure 10 demonstrates the data likelihood for the clay cap defined at $\sigma=0.10$ S/m collocated with steam flow less than 650 m away. In general the two reliabilities are fairly similar to each other; however Figure 10 has slightly more electrical conductance overlap for the steam flow categories. Particularly, the highest steam flow category no longer has conductance's less than 40S and $\theta_i=3$ ($10 < \text{steam flow} < 15$) and $\theta_i=5$ ($15 < \text{steam flow} < 20$) are more alike than the same distributions in Figure 9. Any overlap between distributions signifies that the message of electrical conductance regarding steam flow rate will be uncertain. This will affect the final VOI estimation.

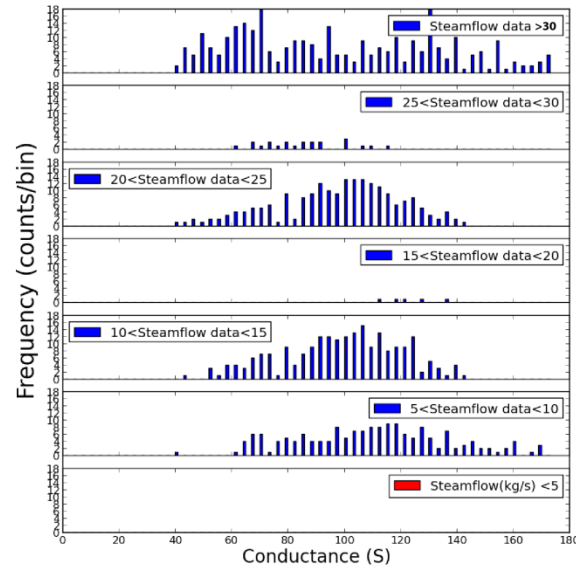


Figure 10: Data likelihood/reliability of clay cap defined by 0.10S/m conductivities within 650m of steam flow magnitude categories. X-axis represents the clay cap electrical conductance (S).

The information posterior is the chronological reverse of the data likelihood (eq. 7):

$$Pr(\theta = \theta_i | G = g_j) = \frac{c_{ij}}{\sum_i c_{ij}} \quad (5)$$

$$i = \{1, \dots, 7\} \quad j = 1, \dots, J$$

where now we have probability of any of the steam flow categories (θ_i) occurring given a particular bin value for the conductance (g_j). Now the denominator, $\sum_i c_{ij}$, is the sum over all steam flow bins for each conductance bin. This is calculated from the raw

counts seen in the histograms of Figures 9 and 10. Figures 11 and 12 plot the posterior over the counts for the two clay caps. The sum of the posterior across all steam flow categories within each conductance bin is 1. The largest difference between the two posteriors is for the highest steam flow category at the lowest conductance values. Any conductance <20 S is given 100% probability of indicating steam flow >30 kg/s in Figure 11, whereas for Figure 12 it is equally probable to be any of the 7 steam flow categories ($1/7 \approx 14\%$). The information posterior is what is used in the $VO_{\text{imperfect}}$ calculation.

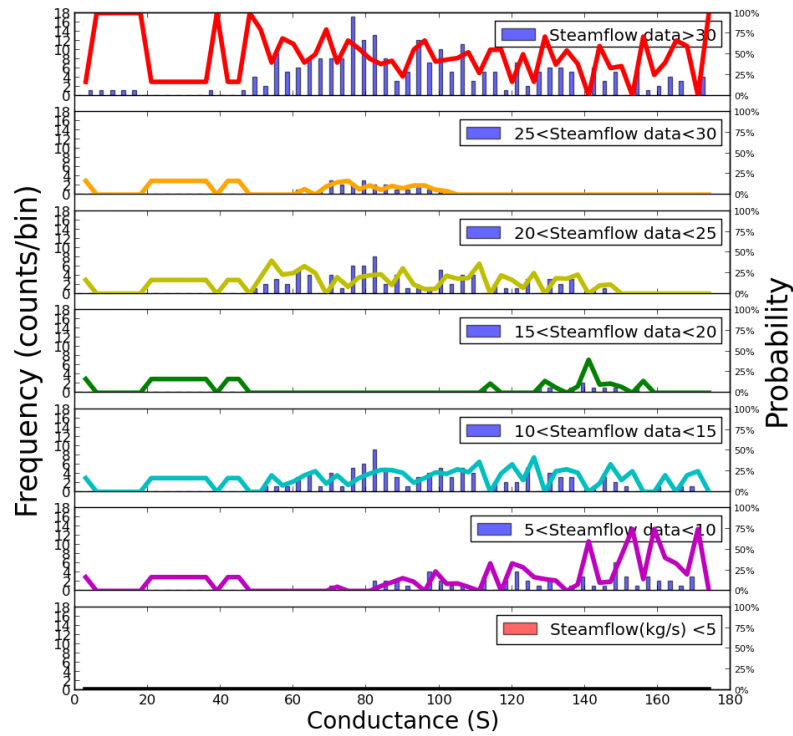


Figure 11: The information posterior (color lines) for the clay cap defined by 0.12S/m conductance within 650m to inform on steam flow magnitude categories. The bars use the same counts from Figure 9.

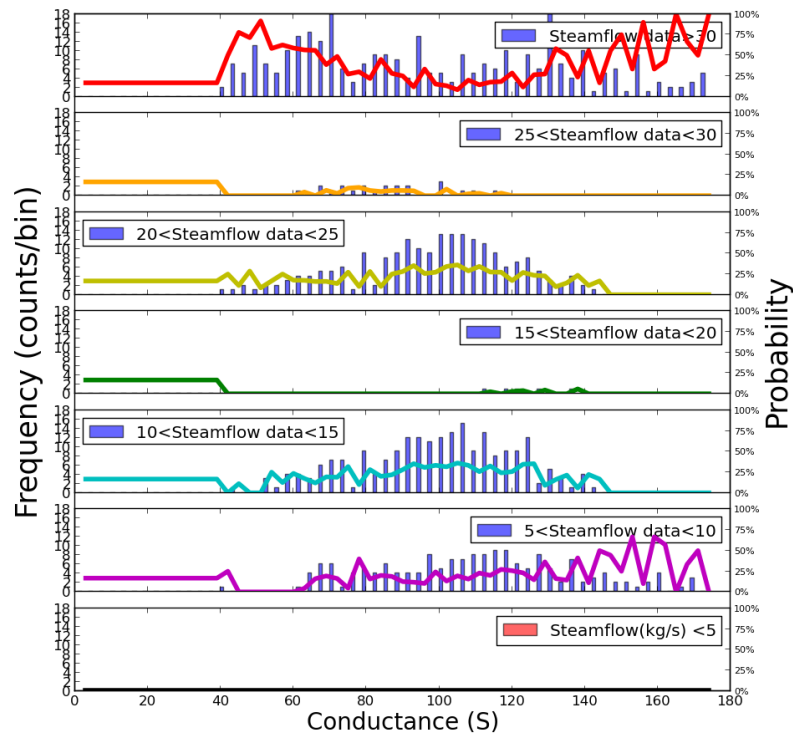


Figure 12: The information posterior (color lines) for the clay cap defined by 0.10S/m conductance within 650m to inform on steam flow magnitude categories. The bars use the same counts from Figure 10.

4. V_{prior} : THE BEST DECISION OPTION GIVEN PRIOR UNCERTAINTY

We will now describe how each prior model is linked to possible economic outcomes. This will be summarized in the quantity V_{prior} , which translates our prior uncertainty (our current state of information) into an expected (or average) outcome from our decision.

Recall that decision analysis frames the decision as the chance to enter the geothermal lottery with perceived chances of winning a prize (e.g. drilling into a profitable reservoir). By utilizing V_{prior} , a decision-maker can logically determine when one should participate in this lottery given both the prior uncertainties and possible gains and losses. The value metric allows for comparison between outcomes from different decision alternatives, which can be represented by function d_a .

$$v_a^{(t)}(\theta_i) = d_a(z(\theta = \theta_i)^{(t)}) \quad (6)$$

$$a = 1, 2 \quad i = 1, \dots, 7 \quad t = 1, \dots, T$$

We assume only 2 possible alternatives ($a = 1$ or 2): drill/produce the reservoir or do nothing. Table 1 defines the 14 possible outcomes, which is a result of these 2 decision alternatives and the 7 possible reservoir categories. The columns represent the decision alternatives ($a=1$ and $a=2$) and the rows the different steam flow categories (θ_i).

Table 1: Table of nominal value outcomes for the 2 possible decision options (columns) and 5 possible economic viability categories of the unknown subsurface (rows).

Decision option→ ↓Steam Flow Rate (kg/s)	$v_{a=1}^{(t)}(\theta_i)$ a = 1 (drill under cap)	$v_{a=2}^{(t)}(\theta_i)$ a = 2 (do nothing)
$30 \leq \theta_i$	\$700,000	\$0
$25 \leq \theta_i \leq 30$	\$300,000	\$0
$20 \leq \theta_i \leq 25$	\$125,000	\$0
$15 \leq \theta_i \leq 20$	\$40,000	\$0
$10 \leq \theta_i \leq 15$	\$0	\$0
$5 \leq \theta_i \leq 10$	-\$200,000	\$0
$\theta_i \leq 5$	-\$500,000	\$0

Table 1 represents hypothetical, monetary values that could represent gains (payouts-- shown in black-- when you produce an economic reservoir) or losses (loss on investment --shown in red--when you drill an uneconomic reservoir). Specific (and more realistic) gains and losses for a particular field site can be easily substituted in Table 1 and into the methodology. This would be necessary to use the resulting VOI's to determine if a particular data type is worth purchasing at a specific field site. The values in Table 1 are simply for demonstration purposes so that the behavior of the VOI quantities can be visualized.

All the necessary quantities have been introduced to calculate V_{prior} .

$$V_{\text{prior}} = \max_a \left(\sum_{i=1}^7 Pr(\theta = \theta_i) v_a(\theta_i) \right) \quad (7)$$

$$a = 1, 2$$

In words, V_{prior} quantifies the best the decision-makers can do with the current uncertainty (no MT data has been collected), which are reflected in the prior probabilities $Pr(\theta = \theta_i)$. V_{prior} identifies which decision alternative gives *on average* the best outcome (done through the max). When considering a specific location for geothermal exploration, these prior probabilities should come from a geologist and/or other experts with knowledge of the geologic structure and history. For now, we assume $Pr(\theta = \theta_1) = 40\%$ (steam flow < 5 kg/s) and all other categories $Pr(\theta = \theta_i) = 10\%$ $i = 2, \dots, 7$. These can be changed and the final VOI will depend on these prior probabilities.

Returning to the lottery example, when V_{prior} is 0, the decision-maker should “not participate in the lottery” (i.e. don’t drill) given the current state of information. $V_{\text{prior}}=0$ tells the decision-maker that the decision alternative to “do nothing” will yield the higher outcome on average. $V_{\text{prior}}=0$ reflects the potential for large losses when you “participate in the lottery” or drill to produce a geothermal reservoir. The decision-maker would only be wise to participate in the lottery when $V_{\text{prior}} > 0$. Given the assigned prior probabilities and the value outcomes of Table 1, $V_{\text{prior}}=\$0$ for this example.

5. VALUE OF PERFECT AND IMPERFECT INFORMATION

The value of perfect information can be calculated using Equation 1, by substituting in V_{perfect} for the value with information ($V_{\text{with information}}$). VOI_{perfect} assumes that an information source exists that will always identify the correct economic viability category θ_i without errors. Like V_{prior} , V_{perfect} only depends on the prior uncertainty and potential gains/losses of the problem.

$$V_{perfect} = \sum_{i=1}^7 Pr(\Theta = \theta_i) \left(\max_a v_a(\theta_i) \right) \quad (8)$$

Here, we see that for each steam flow rate category θ_i , we can choose the best decision alternative a (this is reflected in \max being performed before the average). With perfect information, we always know when the reservoir is uneconomic, and therefore we will always choose not to participate in the lottery. Thus, we remove the chance of loss by collecting perfect information. With our current state of information, we would not enter the lottery when the potential losses were too high relative to the gains. But with a flawless information source to allow us to avoid these losses, we may choose to participate in the lottery. Since it assumes error-free information, the $VOI_{perfect}$ quantity will give an upper bound on what we could expect for any information source. For this example, using the values in Table 1, $V_{perfect} = \$116,500$. Thus, since $V_{prior} = \$0$, $VOI_{perfect} = \$116,500$.

Now we consider imperfect MT data and we estimate its reliability when distinguishing between the seven different possible steam flow categories θ_i . The data is from a specific location, and we are using it to generate the required information posterior, which influences VOI , but everything else (priors, value outcomes, etc.) is completely unrelated to the location and settings of the actual data set. The information posterior is the form actually used to calculate the value *with* imperfect information $V_{imperfect}$.

$$V_{imperfect} = \sum_{j=1}^J Pr(G = g_j) \left\{ \max_a \left[\sum_{i=1}^7 Pr(\Theta = \theta_i | G = g_j) v_a(\theta_i) \right] \right\} \quad (9)$$

Here, the posterior accounts for how often one may incorrectly infer a steam flow category given the inverted electrical conductivity. The posterior is used to weigh the averaged outcome of each alternative and category combination $v_a(\theta_i)$. Since the decision is made after conductivity data has been collected, the best alternative (\max_a) is chosen given the interpreted category.

Lastly, $V_{imperfect}$ is weighted by the marginal probability $Pr(G = g_j)$, how often any of the particular inverted resistivities occur relative to other conductivity bins.

Table 2: Table of **nominal** $V_{imperfect}$ and $VOI_{imperfect}$ for the 2 clay cap interpretations (rows).

Clay Cap defined by threshold:	Max Dist Steam-Cap	$V_{imperfect}$	$VOI_{imperfect}$
0.12 Siemens/m	650m	\$95,855	\$95,855
0.10 Siemens/m	650m	\$93,076	\$93,076

Table 2 includes both the value with imperfect information ($V_{imperfect}$) and the value of imperfect information ($VOI_{imperfect}$). The value of imperfect information is calculated using Equation 1 where now the $V_{imperfect}$ is used in place of the generic term of $V_{imperfect}$. As expected, both $VOI_{imperfect}$ estimates are lower than $VOI_{perfect}$ (\$116,500). This demonstrates how the highest value outcome will not be realized because of the imperfectness of the data that can mislead the decision maker about the economic viability of the reservoir. The two $VOI_{imperfect}$ results are not significantly different from each. But as expected from visually comparing the overlaps in Figures 16 and 17, the $VOI_{imperfect}$ assessed from the clay cap defined at 0.12S/m is slightly higher.

6. CONCLUSIONS AND FUTURE WORK

VOI is used to determine whether a particular type of data is worth acquiring and thus, the VOI must be calculated before the intended data is collected. We use a calibrated data set (electrical conductivity model from MT collocated with steam flow measurements) to estimate the past performance of MT to delineate the boundaries of the clay cap. Therefore, we assume that this VOI will be used to decide whether or not to purchase 3D MT at a analog field site. Specifically, we estimated the reliability of the data to reveal the principal uncertainty to the decision (θ_i representing steam flow for our example). In turn, we described how the value of imperfect information could be calculated with this reliability. We use a hypothetical decision scenario of “to drill or not” to define the other drivers of VOI : the prior probability, the value outcomes of Table 1. These would need to be refined in order to use these VOI estimates to determine whether or not to purchase the information.

These preliminary results illustrate a simplified VOI method that uses calibrated field data: conductivities and thicknesses of a clay cap and steam flow measurements. Future work will look at other production variables such as productivity index. Also, the spatial uncertainty will be included in the future framing of the drilling decision, which will better highlight the value in geophysical information like MT inversions. Much further work needs to be done to incorporate the calibrated data into a spatial decision problem.

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